



Future precipitation variability during the early rainfall season in the El Yunque National Forest

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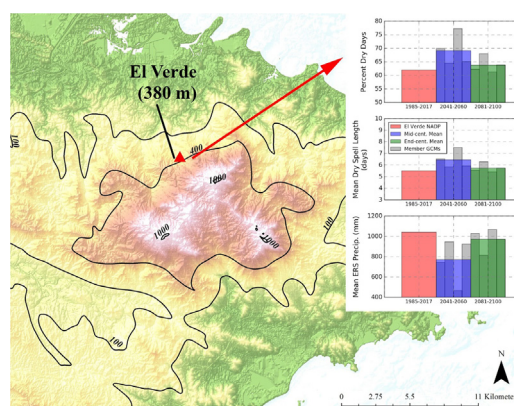
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HIGHLIGHTS

- Uses an ANN to downscale coarse-resolution GCM data to local scale rainfall in ELNF
- The ANN predicts dry day frequency (<5 mm) with 92% percent accuracy.
- 7.2% increase in ERS dry-day frequency by mid-century (2041–2060)
- ~200-mm decrease in ERS rainfall by mid-century
- Dry-day frequency recovers by end-century (2081–2100) back towards current climatology.

GRAPHICAL ABSTRACT



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ABSTRACT

El Yunque National Forest, situated in the Luquillo Mountains of northeast Puerto Rico, is home to a wide range of climate-sensitive ecosystems and forest types. In particular, these ecosystems are highly sensitive to changes in the hydroclimate, even on short time scales. Current global climate models (GCMs) predict coarse-scale reductions in precipitation across the Caribbean prompting the need to investigate future fine-scale hydroclimate variability in the Luquillo Mountains. This research downscales coarse-resolution GCM RCP8.5 predictions from the IPCC CMIP5 project to the local scale to better assess future rainfall variability during the most critical period of the annual hydroclimate cycle, the early rainfall season (ERS). An artificial neural network (ANN) is developed using five field variables (1000-, 850-, 700-, and 500-hPa specific humidity and 1000–700-hPa bulk wind shear) and four derived precipitation forecasting parameters from the ERA-Interim reanalysis. During the historical period (1985–2016), the ANN predicts a binary dry (<5 mm) versus wet (≥5 mm) day outcome with 92% percent accuracy.

When the historical inputs are replaced with bias-corrected data from four CMIP5 GCMs, the downscaled ensemble mean indicates a 7.2% increase in ERS dry-day frequency by mid-century (2041–2060), yielding an ERS dry-day percentage of 70% by mid-century. The results presented here show that the decrease in precipitation and wet-days is, at least in part, due to an increase in 1000–700 hPa bulk wind shear and a less favorable thermodynamic environment driven by increased mid-tropospheric warming and a stronger trade wind inversion. By

Abbreviations: ANN, artificial neural network; ELNF, El Yunque National Forest; ERS, early rainfall season.

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regressing ERS total precipitation against dry-day frequency ($R^2 = 0.95$), the predicted mid-century dry-day proportion corresponds to a ~200-mm decrease in seasonal precipitation. In contrast, the ensemble predicts a dry-day frequency recovery back towards the historical climatological mean by end-century (2081–2100).

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1. Introduction

The ecologically diverse El Yunque National Forest (EYNF), situated in the Luquillo Mountains (LM) of northeast Puerto Rico, is home to a range of climate-sensitive forest types and ecosystems, including a montane cloud forest. The EYNF is punctuated by a steep topographic gradient that subsequently drives a steep precipitation gradient (Fig. 1). Additionally, the LM provide important array of services to the island of Puerto Rico, including tourism and water resource contributions to the municipal water supply for the San Juan Metropolitan area (Crook et al., 2004). Mandatory water rationing on the island occurs frequently during drought periods, including six times in the 1990s, with the most severe drought occurring in 1994, resulting in an economic loss of \$165 million (Lugo and García-Martínó, 1996). The EYNF has been the site of extensive scientific research for the last 40 years, particularly on how the streams, soil, and biology respond to climate variability. Studies have shown these ecosystems, and the biogeochemical cycles that occur within them, to be highly sensitive to changes in precipitation. For instance, droughts can have lasting impacts on plants, animals, carbon and nutrient cycling in the LM (Waide and

Lugo, 1992; Willig and Walker, 1999; Beard et al., 2005; Brokaw et al., 2012; Wood and Silver, 2012; O'Connell et al., 2018; Uriarte et al., 2018).

Dry periods significantly increase soil CO_2 emissions, drive significant declines in inorganic phosphorous, and increase soil respiration in the tropical forests of the EYNF (O'Connell et al., 2018). Drought drives soil moisture decreases in the forest, sometimes as large as 63%, and soil moisture is slow to recover after a drought (O'Connell et al., 2018). In some cases, the drought recovery period was ~65% of the length of the drought period which indicates that impacts of drought may persist well beyond when precipitation increases (O'Connell et al., 2018). Similarly, ecological modeling experiments predict large shifts in forest composition under a warmer and drier climate scenario with drought projected to drive net forest productivity to zero by 2036 (Feng et al., 2018). Dry periods also lead to increased litterfall and decreased root biomass (Beard et al., 2005).

Droughts have also been shown to significantly change habitat structure and trophic dynamics in LM streams (Covich et al., 2003, 2006), and drought-related streamflow reductions also create barriers for migratory species in the forest (Pringle, 1997; Benstead et al., 1999; Covich et al., 2006). Short-term dry periods have been linked to declines in the abundance of common lizards, spiders, and exotic

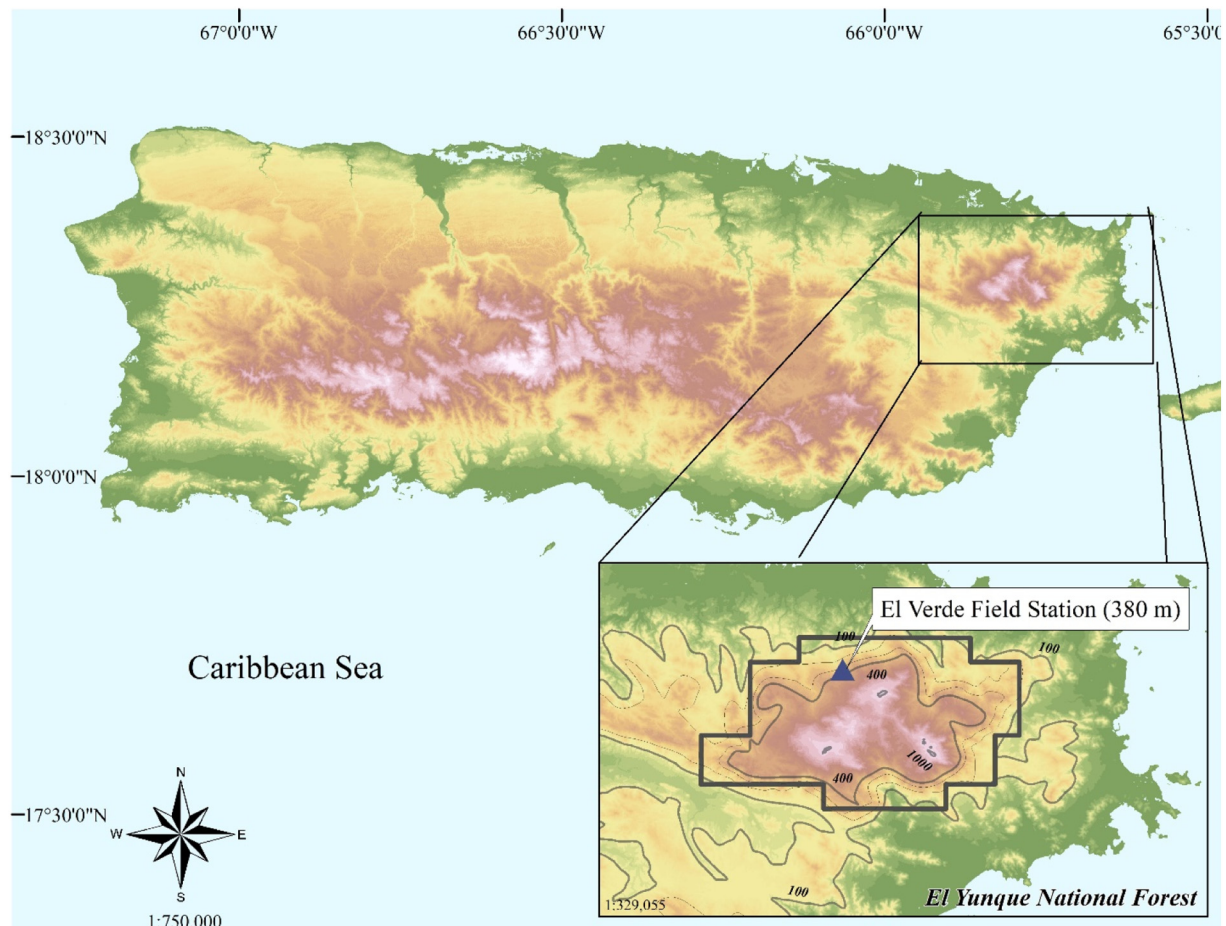


Fig. 1. Topographic map showing the location of the El Verde NADP rain gauge. The inset map also shows the boundary of the El Yunque National Forest (bold).

earthworms (Reagan and Waide, 1996; Zou and González, 1997). When a dry spell lasts 3 days, tree frogs in the forest have empty stomachs because of the lack of insects that normally occur on the wet forest floor (Covich et al., 2006). One week without precipitation causes a wilting of herbaceous vegetation (Covich et al., 2006). These serve as examples of how the biological and biogeochemical cycles in the rainforest have been shown to be highly sensitive to short duration dry spells, on the order of a few days (O'Connell et al., 2018). Consequently, any changes to dry-day frequency and seasonal precipitation totals in EYNF will represent important sources of ecological disturbance in future decades.

Precipitation variability in Puerto Rico, like all islands in the Eastern Caribbean, is largely controlled by synoptic- and global-scale wave patterns, tropical cyclones, regional wind patterns, sea-breeze circulations, intense solar heating, and orographic effects (Taylor et al., 2002). The spatial pattern of rainfall across Puerto Rico is strongly associated with topography, exposure to predominant winds, and proximity to the ocean (Daly et al., 2003). For instance, in Eastern and Central Puerto Rico, precipitation increases at an approximate rate of 140% per kilometer change in elevation (Daly et al., 2003). Island-wide, the area of highest precipitation is the steep, east facing slopes of the LM where moisture-laden air is orographically forced to its lifting condensation level (Comarazamy and González, 2008; Daly et al., 2003; Jury, 2009; Miller et al., 2018, 2019). By corollary, changes to the predominant winds lead to the redistribution of localized moisture convergence and changes in rainfall patterns (Comarazamy and González, 2011). Additionally, low- and mid- tropospheric wind shear has been shown to disrupt nascent convection, leading to lower precipitation in the LM (Enfield and Alfaro, 1999; Ramseyer and Mote, 2016, 2018). Meanwhile, the trade-wind inversion and its modification due to Saharan Air Layer intrusions can further limit precipitation by creating a vertical layer of thermodynamic stability (Mote et al., 2017).

Given the unique superposition of global, synoptic, and local-scale factors governing EYNF hydroclimate, high-resolution future climate studies are needed to understand the precipitation regime changes expected to occur in the LM. However, GCMs are unable to resolve the steep precipitation gradient in the LM due to their coarse spatial resolution (Scholl and Murphy, 2014), and even convection-permitting regional climate models struggle in the LM's complex terrain (Bhardwaj et al., 2018). GCMs have been shown to capably resolve synoptic-scale wind fields, temperature, and moisture that are important for precipitation in the LM (Ramseyer and Mote, 2016, 2018).

This study addresses the need for high-resolution hydroclimatic data for the future in the El Yunque National Forest. This study downscales future precipitation scenarios for the early rainfall season (ERS) from coarse GCM predictions using an artificial neural network (ANN). The ANN relates GCM-derived atmospheric variables to predict a binary wet- versus dry-day outcome at El Verde Field Station within EYNF, with the projected dry-day frequency serving as the basis for future ERS precipitation totals.

2. Data and methods

The ERS drives much of the annual precipitation variability in Puerto Rico (Miller et al., 2018, 2019), and it also serves as the recovery period for the region after the dry season spanning December–March (Van Beusekom et al., 2015). For instance, the 2015 Puerto Rico drought, one of the worst on record, was largely a result of historically low rainfall totals during the ERS (Mote et al., 2017).

In climate downscaling research methodologies, ANNs are employed to derive nonlinear relationships between coarse atmospheric and oceanic data inputs and a local variable (e.g. temperature, rainfall). ANNs are now widely used in precipitation studies due to their ability capture the nonlinearities between atmospheric predictor variables and precipitation (Hall et al., 1999; Bellerby et al., 2000; Sahai et al., 2000; Schoof and Pryor, 2001; Cavazos and Hewitson, 2005; Moustris et al., 2011; Ramseyer and Mote, 2016; Valipour, 2016). ANNs have been shown to

outperform other statistical downscaling techniques when modeling precipitation (Kuligowski and Barros, 1998; Valverde Ramírez et al., 2005). Additionally, the ANN weight matrix yields information on which predictor variables are most important in the model (Olden and Jackson, 2002; Ramseyer and Mote, 2016). There are several statistical downscaling techniques that can be leveraged for climate downscaling studies (Sachindra et al., 2018a,b; Winkler et al., 2011). ANNs were used in this study because of its demonstrated performance in modeling precipitation broadly (Kuligowski and Barros, 1998; Valverde Ramírez et al., 2005) and specifically at this research site (Ramseyer and Mote, 2016, 2018).

2.1. Observed precipitation in EYNF

Daily precipitation data for the ERS were acquired from the National Atmospheric Deposition program (NADP) for the period 1985–2016 for the El Verde, PR, station (National Atmospheric Deposition Program, 2018). The data were converted to a binary wet- (≥ 5 mm) versus dry-day (< 5 mm) sequence with the wet/dry-day outcome serving as the ANN variable of interest. Historically, dry days constitute 62% of all days during the ERS in EYNF. A monthly hydroclimatology of the site for the ERS is included in Fig. 2.

2.2. ANN configuration and optimization

The predictive capability of an ANN is dependent on the selection of appropriate predictor variables. A total of nine atmospheric inputs were used to train the ANN, five field variables and four derived quantities. The five field variables, low- and mid-tropospheric moisture and 1000–700-hPa bulk wind shear (BWS), have been previously identified as effective predictor variables of precipitation in the region (Ramseyer and Mote, 2016, 2018). As such, 1000, 850, 700, and 500 hPa daily specific humidity as well as 1000 and 700 hPa u- and v- wind data were acquired from the 0.25°-resolution ERA-Interim reanalysis (Dee et al., 2011) grid point containing the El Verde NADP rain gauge.

BWS is calculated by first determining meridional and zonal shear. Meridional shear (MS) is the difference in the v-wind at two atmospheric levels:

$$MS = |V_{1000} - V_{700}| \quad (1)$$

Zonal shear (ZS) is calculated as the difference in the u-wind at two atmospheric levels:

$$ZS = |U_{1000} - U_{700}| \quad (2)$$

BWS is then calculated as the vector:

$$BWS = \sqrt{MS^2 + ZS^2} \quad (3)$$

Four derived quantities were also integrated into the ANN, daily values of the Gálvez-Davison Index (GDI) and its three component terms. The GDI, an experimental forecasting tool with precedent in climatological research (Mote et al., 2017), was calculated as prescribed by Gálvez and Davison (2016) using ERA-Interim reanalysis from the same grid point contributing the field variables. This recently developed index has been shown to effectively diagnose convective potential in the tropics and outperforms other convective indices often used in the mid-latitudes (Gálvez and Davison, 2016). The GDI calculation incorporates 1000-, 950-, 700-, and 500-hPa specific humidity and temperature, and is the sum of three component terms: the column buoyancy index (CBI), a mid-level warming index (MWI), and a trade-wind inversion index (II). Because each GDI component is tied to a physically meaningful convective process, the three components, in addition to the GDI itself, were included in the model to more explicitly resolve important features of the tropical atmosphere. In particular, II is a measure of the strength of the trade wind

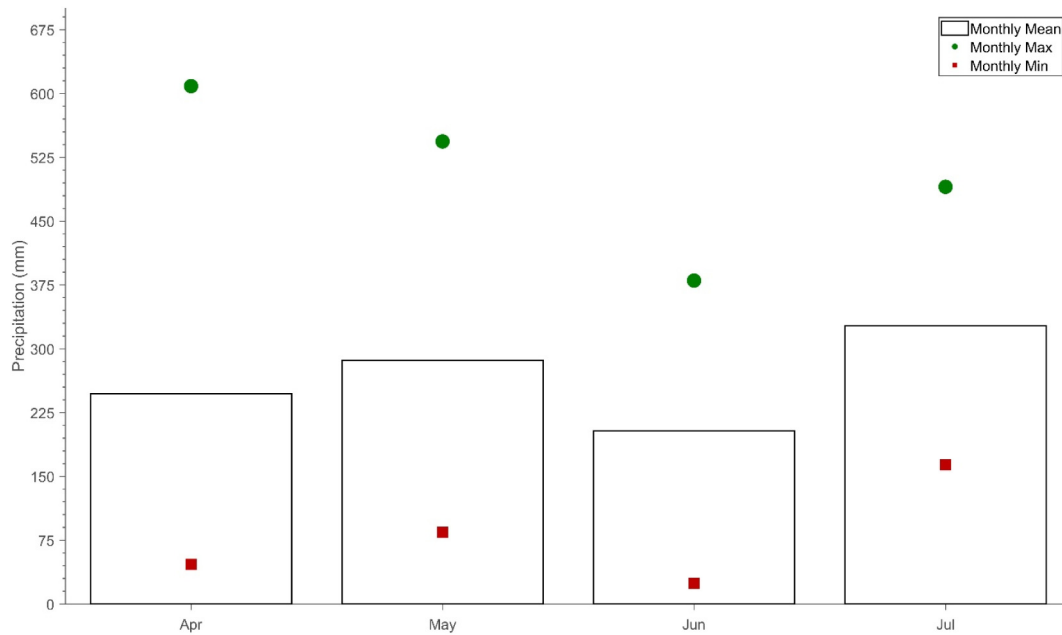


Fig. 2. Monthly hydroclimatology of the El Verde NADP rain gauge for the ERS.

inversion, and important stabilizing mechanism in the Caribbean and tropical North Atlantic as well as a driver of drought in Puerto Rico (Gutnick, 1958; Mote et al., 2017; Schubert et al., 1995).

A suite of experiments were run to determine the optimal architecture and weightings for the ANN. These ANNs were constructed in MATLAB to predict ERS wet/dry days at El Verde, PR. ANNs and other statistical downscaling techniques have been shown to produce unphysically large outliers (Sachindra et al., 2018b). This methodology avoids some of these shortcomings by confining the output from the ANN to [0–1] where a 0/1 indicates a dry/wet day.

The initial experiments tested several ANNs with varying numbers of hidden nodes. The most effective ANN architecture, which

utilized 50 hidden nodes and gradient descent minimization, was selected due to its sufficient predictive ability and reasonable computational cost. The ANNs with node architectures over 50 had minimal performance improvements but large increases in computational cost. After determining the optimal number of hidden nodes, 250 ANNs were created using varying initial conditions and training data. ANNs trained with subsets of the nine input variables experienced a reduction in predictive capability. For each ANN, 1000 training iterations progressively updated the weight matrix to its final form. The data were randomly assigned to a training index (70% of the available data), validation index (15%) and test index (15%). This allowed for analysis of the both the training and test

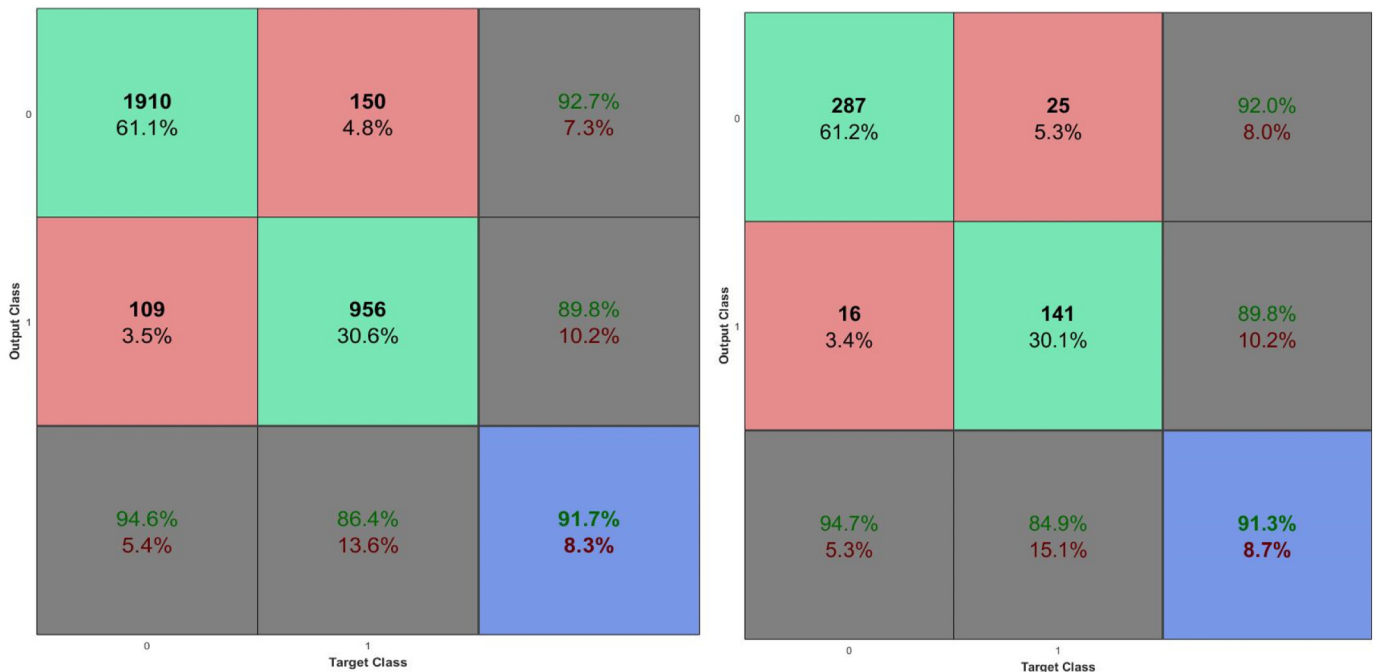


Fig. 3. Contingency table for the training data (left) and the randomly selected test data (15% of available data vectors, right panel). Dry days and wet days correspond to classes 0 and 1, respectively.

index, to ensure the model data were not overfitting the training data. The most accurate model configuration of the 250-ANN suite achieved a hit rate of 91.7% on the training data (Fig. 3, left panel) and 91.3% on the test data (Fig. 3, right panel). This ANN was subsequently selected to downscale the CMIP5 future data.

To ensure that the contingency table was a representative metric of the performance of the ANN, other performance indicators were calculated. The critical success index (CSI) is often used by the National Weather Service as an indicator of the value of watches and warnings and can be used for other dichotomous forecasts (Donaldson et al., 1975). CSI measures the fraction of observed and/or forecast events that were correctly predicted, it is sensitive to hits and penalizes for both misses and false alarms. CSI has a range of 0 to 1, with 0 indicating no skill. The CSI for the ANN presented here is 0.8015. This indicates that ~80% of the observed and/or predicted rain events were correctly forecast.

CSI can be biased for low frequency events and can overestimate the skill of a forecast since some correct forecasts can occur due to random chance, thus, an additional verification index was used to ensure the accuracy of the model is correctly represented (Schaefer, 1990). The Gilbert Skill Score (GSS) is often used in verification of rainfall in numerical weather prediction models and can be an improvement over CSI in some cases as it adjusts for hits associated with random chance (Schaefer, 1990). GSS effectively measures the fraction of observed and/or forecast events that were correctly predicted with the adjustment for random chance (Schaefer, 1990). The GSS for the ANN presented here is 0.7124 on a scale from $-1/3$ to 1, where 0 indicates no skill.

2.3. CMIP5 data acquisition and bias correction

Four GCMs had complete records of all data needed to run the ANN. They are the Beijing Climate Center – Climate System Model (BCCB1),

Canadian Centre for Climate Modelling and Analysis Earth System Model (CCE2), Institut Pierre Simon Laplace CM5A Model (IPSL), and the National Center for Atmospheric Research Community Climate System Model (NRS4). Data were downloaded from the World Data Center for Climate (WDCC), hosted by the German Climate Computer Center (DKRZ) and separated into two epochs, a mid-century epoch from 2041 to 2060 and an end-century epoch from 2081 to 2100. Daily 1000-, 850-, 700-, and 500-hPa specific humidity and 1000- and 700-hPa u- and v- wind data for both the historical and future RCP8.5 simulations were extracted for the grid point containing EYNF. Meanwhile, the GDI and its subcomponents were also calculated using CMIP5 daily data with the exception of the 950-hPa height level, which is required for the GDI computation but not readily available in CMIP5 daily files. For this level, six-hourly historical and future RCP8.5 temperature and specific humidity data on native model levels were vertically interpolated and averaged by day to complete the GDI calculation.

All model data were bias corrected using a distribution mapping approach. Distribution mapping has been shown to produce superior corrections compared to other methods, particularly when the corrected data are subsequently combined to predict a derived quantity (Teutschbein and Seibert, 2012). Conceptually, all distribution mapping methods attempt to adjust the modeled values so that their distribution more accurately resembles that of the observed data for the same variable. Though a variety of such techniques have been proposed (McGinnis et al., 2015), this study employs a simple form of distribution mapping, known as quantile mapping, as implemented by the R package qmap (Gudmundsson, 2016). In this approach, the bias is obtained using empirical percentiles determined from the cumulative distribution functions of both the observed and modeled data. Figs. 4–5 depict the result of the quantile mapping correction applied to 1000-hPa specific humidity and 1000–700-hPa wind shear, respectively. The bias-corrected temperature and specific humidity data were used to calculate the GCM-predicted GDI values.

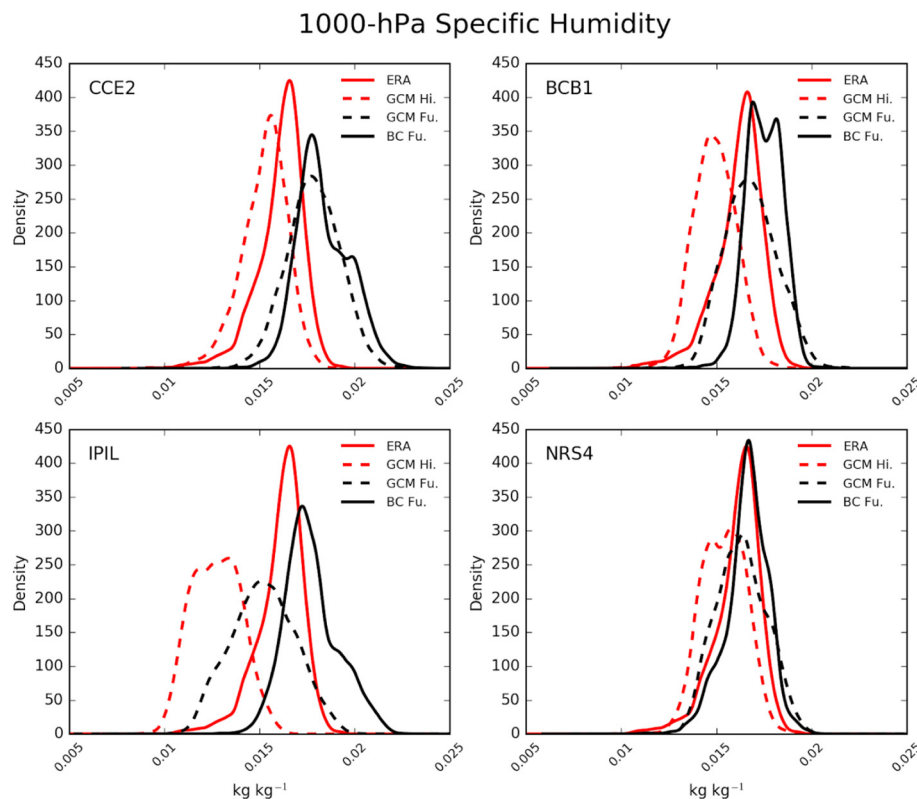


Fig. 4. 1000-hPa specific humidity biases as shown by differences in ERA-Interim (red, solid) and GCM historical runs (red, dashed). Future, non-bias-corrected 1000-hPa specific humidity (black, dashed) and bias-corrected future 1000 hPa specific humidity (black, solid).

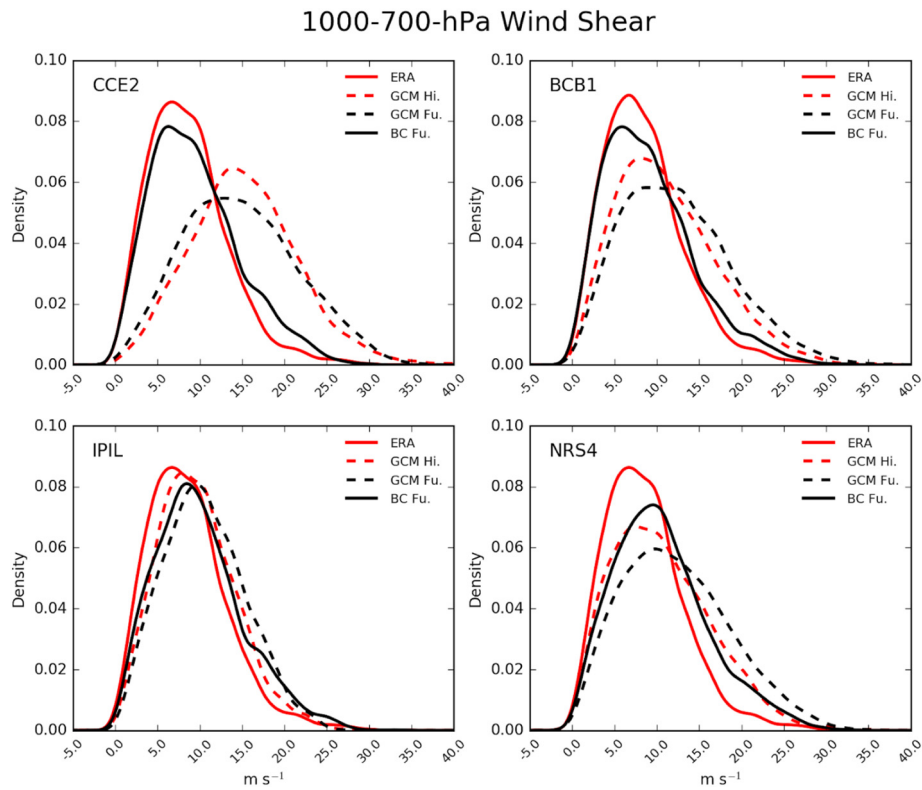


Fig. 5. 1000–700-hPa BWS biases as shown by differences in ERA-Interim (red, solid) and GCM historical runs (red, dashed). Future, non-bias-corrected BWS (black, dashed) and bias-corrected future BWS (black, solid).

The results of the quantile mapping bias correction on the CMIP5 data indicate biases are present between all variables in the historical GCMs and the ERA-Interim reanalysis data, and highlights the necessity of bias correcting GCM data when performing downscaling studies. The GCMs have a dry bias at the study site, particularly at 1000 hPa, with the magnitude of the bias varying by model (Fig. 4). This finds consilience with prior studies that have indicated a dry bias in the low-troposphere in CMIP5 models (Tian et al., 2013). The IPSL has the largest dry bias, while the other three models have more modest dry biases. The GCMs all have a positive 1000–700-hPa BWS bias. CCE2 and BCB1 have the largest bias while the IPSL and NRS4 have small, positive BWS biases (Fig. 5). Temperature data were also bias corrected because they contribute to the GDI, CBI, II, and MWI computations. All four GCMs show cold biases at all four levels analyzed (950, 850, 700, and 500 hPa) with the cold bias generally decreasing at lower pressure levels (i.e., higher altitudes). The IPSL tends to have the strongest cold bias at all levels.

3. Results

3.1. ANN predictor importance

Before presenting the results of the downscaling procedure, the contribution of each ANN predictor to the final weighting structure is provided to better understand the physical processes governing wet/dry day frequency in EYNF. As described in Section 2, the ANN employed nine predictor variables: GDI, CBI, MWI, II, 1000–700-hPa bulk wind shear, and specific humidity at 1000, 850, 700, and 500 hPa. The relative importance of each predictor to the ANN was calculated from the weighting structure between (1) the input nodes and the hidden layer and (2) the hidden layer and the output layer (Olden and Jackson, 2002; Ramseyer and Mote, 2016). Table 1 displays the results of the weighting analysis, and emphasizes the importance of low- and mid-

tropospheric moisture in the model. All four moisture levels rank as the most important ANN variables with BWS also included in the top five. These results find consilience with other statistical downscaling studies in the region (Ramseyer and Mote, 2016, 2018). All four GDI related variables were the four least important variables in the model. However, even CBI, the least important variable, had a relative importance of 6.6%. When removed from the ANN, a decrease in performance was observed. Despite lower relative importance, the GDI and its sub-components increase the overall predictive performance on the ANN.

3.2. Relationship between dry-day frequency and ERS precipitation outcome

In order to apply the ANN-predicted dry-day frequencies to inform ERS precipitation totals, some relationship between ERS dry-day percentage and total precipitation is required. Fig. 6 illustrates a basic, yet compelling, linear regression analysis between ERS dry-day frequency and contemporaneous precipitation, whereby fewer ERS dry days correspond strongly with larger precipitation totals. Further, the relationship

Table 1

The relative importance of each of the predictor variables in the ANN.

Variable	Relative importance (%)
1000 hPa specific humidity	15.4
700 hPa specific humidity	12.4
850 hPa specific humidity	12.2
1000–700 hPa bulk wind shear	12.1
500 hPa specific humidity	11.5
II	10.8
MWI	10.3
GDI	8.8
CBI	6.6

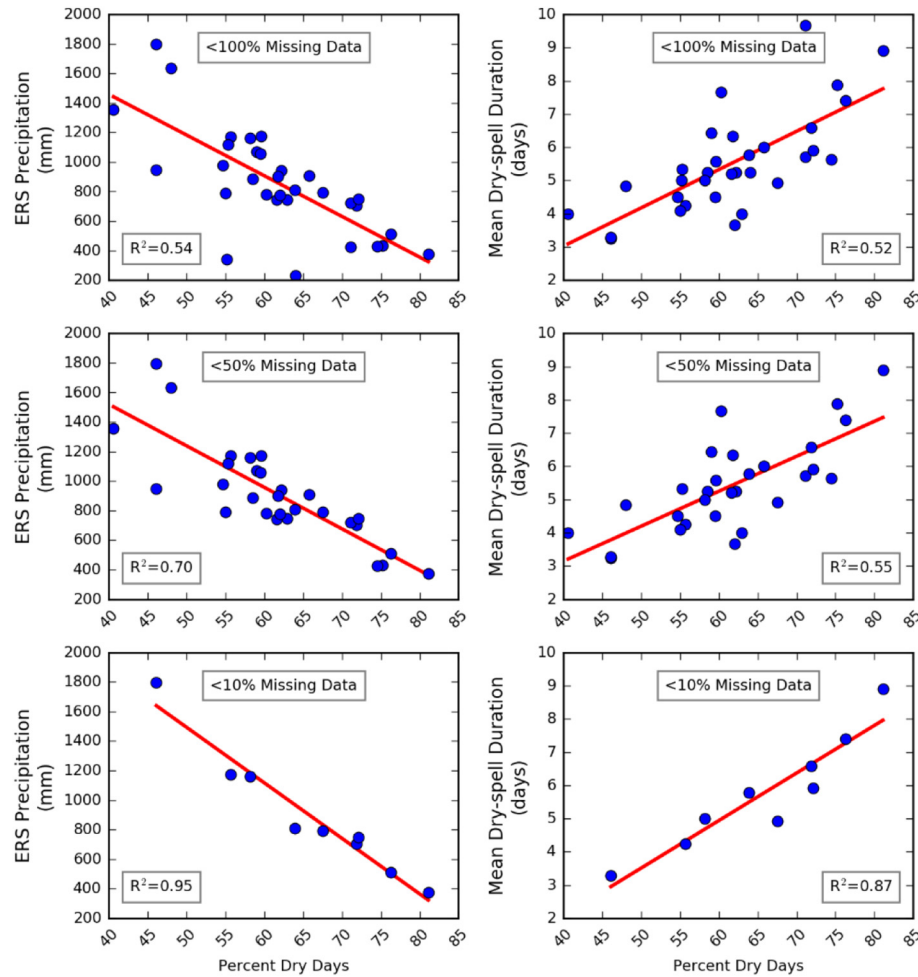


Fig. 6. Linear regression analysis comparing historical ERS seasonal precipitation (left-column) and historical ERS mean dry-spell length (right-column) with ERS dry-day frequency. Days with missing data were excluded from the frequency calculations.

becomes stronger when years with greatest data coverage are subsetting. When analyzing only those ERSs with <10% missing data, the R^2 value of the regression model is 0.95, compared to a R^2 of 0.54 when using data from all ERSs. Given the strength of this relationship, the linear regression equation derived from Fig. 6c (Eq. (4)) will be applied to ANN predictions of future CMIP5-member dry-day frequencies to infer the corresponding EYNF precipitation total.

$$\text{ERS precipitation (mm)} = 3373 - 37.6 * (\text{ERS Dry Day Percentage}) \quad (4)$$

Based on Eq. (4), the mean ERS rainfall at mid-century will decrease by 26% from 1042 mm to 771 mm. By end-century, projected ERS rainfall will rebound to 974 mm, representing a 7% deficit from historical rainfall totals.

3.3. Future ERS dry-day frequency and dry-spell length

The CMIP5 ensemble indicates a 7.2% increase in dry-day frequency by mid-century and a recovery back towards the observed period by end-century (Fig. 7). Stated differently, dry days will constitute nearly 70% of the ERS by mid-century and 64% of the ERS by end-century, compared to the 62% historical (1985–2016) frequency. The IPSL model predicts the largest increase in dry-day frequency by mid-century, with a 14% increase compared to the observed historical period. The CCE2 and NRS4 models predict the smallest increases in dry days, 2% and 3% respectively. The trends from mid- to end-century in the BCB1, IPSL, and NRS4 models are all similar in that they note a decrease in dry-

day frequencies towards the observed historical conditions. The exception is the CCE2 model which shows a continued increase between mid- and end-century. The net ensemble change from observed to end-century is negligible.

The temporal sequencing of data can be disrupted when using quantile mapping bias correction, thus the dry-day sequencing from the ANN cannot be reliable (Sachindra et al., 2014). To be able to reliably discuss modifications in dry-day sequencing patterns, (i.e., more frequent occurrences of consecutive dry days), a regression relationship is developed between the historical ERS mean dry-spell length as a function of dry-day frequency (Fig. 6e). The resulting regression relationship (Eq. (5))

$$\begin{aligned} \text{ERS Mean Dry-spell length (days)} \\ = -2.61 - 0.13 * (\text{ERS Dry Day Percentage}) \end{aligned} \quad (5)$$

The CMIP5 ensemble indicates a roughly one-day increase in the average length of dry spells, defined here as three or more consecutive dry days, by mid-century. The ensemble mean dry-spell length increases from 5.5 to 6.4 days at mid-century before decreasing to 5.7 days by end-century. The IPSL model is an outlier and predicts an increase to over 7 days by mid-century. The ensemble mean suggests a decrease in the dry-spell length from mid- to end-century which results in an increase in dry spell length of 0.2 days compared to the historical period. All ensemble members agree on the return back towards the historical period, except for the CCE2 which suggests a continued increase in dry-spell length from mid- to end-century.

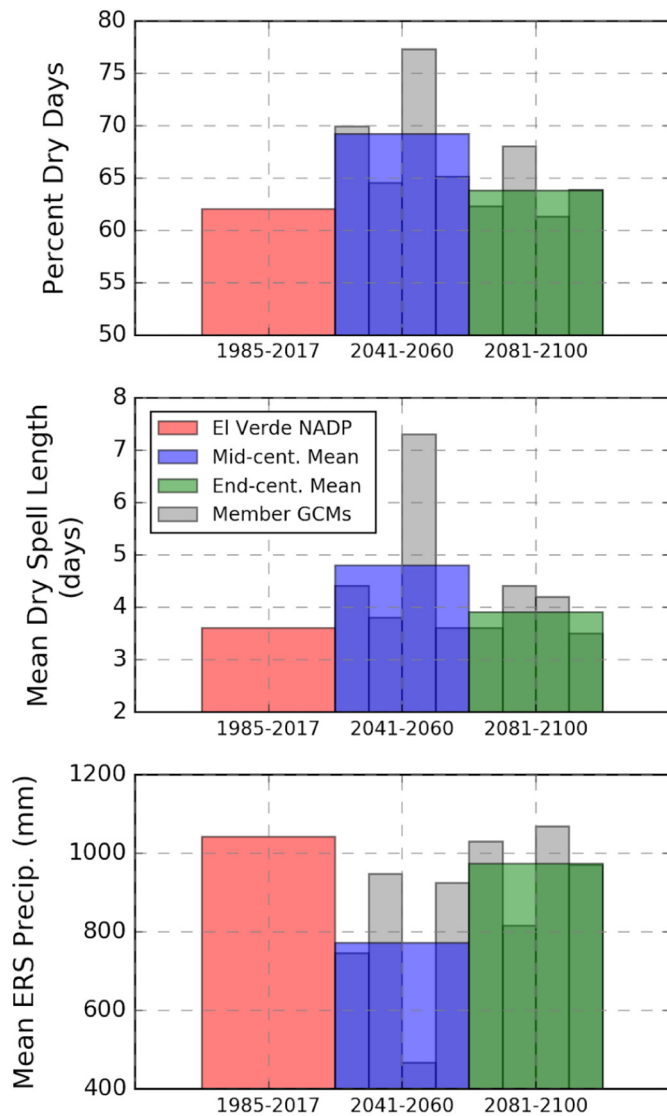


Fig. 7. Changes in dry day frequency (top), mean dry-spell length (middle), and mean ERS precipitation (bottom) between climatology (pink), mid-century CMIP5 ensemble (blue), and end-century CMIP5 ensemble (green). Ensemble members are indicated by gray bars behind ensemble data in the following order, BCB1, CCE2, IPSL, NRS4.

3.4. Future ERS total precipitation and sub-seasonal variability

Using the linear regression model presented in Eq. (4), mean ERS precipitation was calculated for mid- and end-century (Fig. 7). The ensemble average decrease in ERS precipitation from the observed period to mid-century is >200 mm, representing a nearly 20% reduction in precipitation by mid-century. As expected based on dry-day frequency predictions, IPSL is the outlier predicting a mean ERS precipitation of under 500 mm, representing a 50% decrease. The end-century precipitation recovery remains, although the net change by end-century still represents a decrease from historical totals. The CCE2 is the only model predicting a decrease in precipitation in from mid- to end-century, with a decrease of approximately 150 mm over that period.

Changes in dry-day frequency are also analyzed on the monthly timescale (Fig. 8) with all months experiencing an increase in dry-day frequency by mid-century. July is predicted to experience the largest increase with a change of 10%. However, the variability between ensemble members is greatest in for this month as well. Two of the

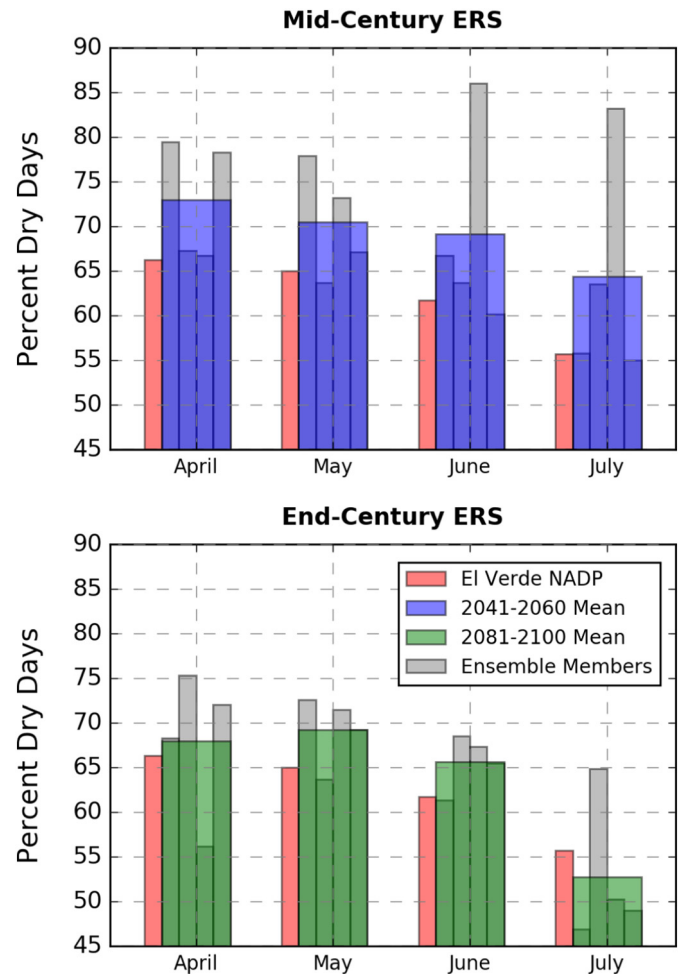


Fig. 8. Dry-day frequencies by month during the ERS comparing the observed historical frequency (pink) to the ensemble averages for mid-century (blue) and end-century (green). Ensemble members are indicated by gray bars behind ensemble data in the following order, BCB1, CCE2, IPSL, NRS4.

ensemble members predict little to no change in July dry-day frequency at mid-century with the 10% ensemble-predicted increase being driven predominantly by the IPSL outlier. The IPSL model is similar to the other three ensemble members in April and May but becomes a noticeable outlier by June. The other three months are all predicted to see increases in dry-day frequency ranging from 5 to 8%.

From mid- to end-century, the ensemble average represents a decrease in dry-day frequency (i.e., more wet days) for all months, though the recovery is tempered in May. The April ensemble mean predicts that end-century dry-day frequency will recover towards historical levels with only one dissenting member, the CCE2. The June ensemble-average dry-day frequency also decreases from mid- to end-century, although two ensemble members, the CCE2 and NRS4, increase June dry days over this period. The ensemble mean decrease for this month is largely driven by the IPSL model, which predicts decreases of ~17%. The largest dry-day decrease is projected in July, again driven primarily by the IPSL model which decreases dry-day frequency by nearly 35% over the period. However, the CCE2 model increases dry-day frequencies from mid- to end-century. The ensemble mean indicates there will be more wet days in July by end-century compared to the observed period.

Whereas the CMIP5 ensemble reduced dry-day frequency from mid- to end-century for most of the ERS, the frequency for May shows little change. As a result of this non-uniform precipitation recovery, the ERS will exhibit a fundamentally different seasonality by end-century.

Instead of dry days peaking in April and then gradually reducing during the subsequent three months, ERS dry days will increase from April to May before decreasing from May to July. Though the ERS will have recovered to near historical precipitation values on an aggregate level, the end-century ERS will be compressed with April and May resembling the preceding dry season (December–March) and July resembling the following late rainfall season (August–November).

4. Discussion

The ANN produced here and used for downscaling the CMIP5 data predicts ERS wet- and dry-day frequencies in EYNF with 91.3% accuracy using a suite of nine climate variables, including low- and mid-tropospheric specific humidity, 1000–700 bulk wind shear, and a tropical convective index and its subcomponents. This ANN weight structure indicates that the specific humidity variables have the largest weights, and thus, are most important to the predictive capability of the model.

The downscaled projections of rainfall suggest that ERS dry days will become more common in the EYNF by mid-century with the increases likely to impact all four months of the season. These changes are primarily driven by increases in 1000–700-hPa bulk wind shear (Table 2) and temperature throughout the low- and mid-troposphere. Warmer low-tropospheric temperatures drive a decrease in the GDI (Table 2) indicating a net reduction in the thermodynamic potential for tropical convection. However, the GDI components contain opposing thermodynamic signals. The reduction is driven by increases in the magnitude of the two inhibition terms, the MWI and II (Table 2), which physically correspond to mid-level (i.e., 500 hPa) warming and a stronger trade wind inversion. Meanwhile, the CBI, designed to capture the vertical concentration of heat and humidity that is favorable for convection, also increases (Table 2). In other words, convective potential increases, but so do the mechanisms that prevent this potential from being realized. Thus, interpreting the net change in convection and convective precipitation is challenging. Of the three GDI components, only the CBI demonstrated significant correlations with radar-indicated echo tops during the ERS (Miller et al., 2018, 2019). Anomalous increases in the magnitude of the II term in particular have tied to severe drought in eastern Puerto Rico (Mote et al., 2017). Within the context of this study, the GDI and its components were the least heavily weighted in the ANN dry-day prediction (Table 1).

Although the GDI shows a sustained net decrease from historical to mid- to end-century, the continued lower-troposphere moistening and CBI increase may represent important physical changes facilitating the precipitation recovery by 2100. The primary drivers of the end-century recovery appear to be increased moisture throughout the low- and mid-troposphere coupled with modest changes in the kinematic environment (Table 2). While increases in moisture and wind shear are also noted from the historical to mid-century period, the wind shear increase from mid- to end-century is overcome by simultaneous moistening occurring throughout the column. At a coarser scale, CMIP5 RCP8.5 GCMs predict a 10–40% end-century precipitation

decrease in Puerto Rico between April–September (Stocker et al., 2013). The results of this study suggest that the unique orographic forcing of the LM will promote the realization of near-surface buoyancy introduced by low-tropospheric moistening, tempering EYNF end-century precipitation deficits compared to surrounding areas. Though the mid-century epoch also experiences moistening, this effect is apparently offset by projected increases in wind shear.

This study also highlights the importance of dry-day frequency as it relates to total precipitation during the ERS. For years with nearly complete records, ERS total precipitation is highly correlated with dry-day frequency. While the ANN does not predict precipitation amount, seasonal precipitation changes can be inferred by leveraging the strong linear regression relationship shown in Eq. (4) and Fig. 6. Based on Eq. (4), the mean ERS rainfall at mid-century will decrease by 26% from 1042 mm to 771 mm. By end-century, projected ERS rainfall will rebound to 974 mm, representing a 7% deficit from historical rainfall totals. Additionally, the model prediction of wet and dry days allows for analysis of mean dry-spell length (Fig. 9). Dry-spell length is an important metric for the biological and biogeochemical cycles in the rainforest that are highly sensitive to even short-term dry spells (O'Connell et al., 2018). At both mid- and end-century, dry-spell duration increases with recovery towards historical sequencing by end-century.

5. Conclusion

Due to the sensitivity of the ecosystems and forests of the EYNF to changes in precipitation, particularly dry spells, it is critically important to understand local-scale precipitation changes under future climate scenarios. This study produces high-resolution downscaled predictions of wet- and dry-day frequencies for the ERS using an ensemble of four CMIP5 GCMs. The ANN-based statistical downscaling methodology predicts wet- and dry-day outcomes with 92% accuracy during the historical period (1985–2016). This approach is particularly valuable given the

Table 2
Changes in each of the predictor variables for the historical period, taken from ERA-Interim reanalysis, and the CMIP5 ensemble-predicted values for the mid-century and end-century temporal periods.

	Historical	Mid-century	End-century
GDI	1.91	−0.27	−2.17
CBI	47.28	64.31	92.26
MWI	−27.43	−42.00	−65.43
II	−17.93	−22.57	−29.00
1000 hPa SH (g/kg)	15.10	16.94	18.14
850 hPa SH (g/kg)	10.14	10.25	10.66
700 hPa SH (g/kg)	4.66	4.67	5.13
500 hPa SH (g/kg)	1.43	1.61	1.88
1000–700 BWS (kts)	7.40	9.56	10.02

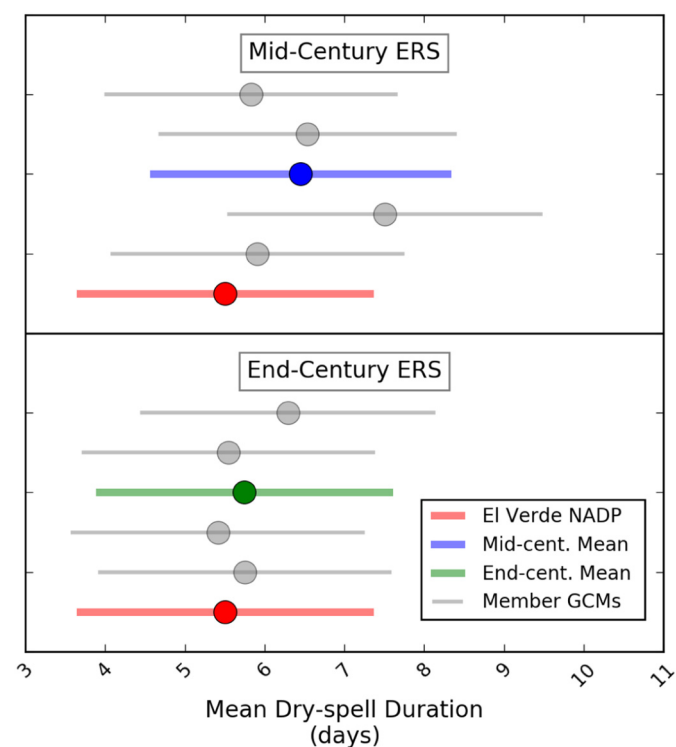


Fig. 9. Confidence intervals of mean dry-spell length from the historical period (red) compared to the predicted CMIP5 ensemble members (gray) for mid-century (top) and end-century (bottom) RCP8.5 scenarios. The intervals represent the 95% confidence level.

strong relationship between historical dry-day percentage and ERS total rainfall (Fig. 6).

The results of this study show that dry-day frequency in the EYNF will increase 7% by mid-century before recovering towards the historical values by end-century. Extending the dry-day frequencies to precipitation impacts, a 26% mid-century reduction in ERS precipitation is predicted with a recovery towards the historical hydroclimate by end-century (7% net reduction). Mean dry-spell length increases from 5.5 to 6.4 days at mid-century before decreasing to 5.7 days by end-century.

In sum, robust changes to the ERS rainfall regime in EYNF are projected to occur by mid-century with an alleviation of those changes by end-century. The precipitation deficits are posited to adversely impact biotic populations in EYNF, and adaptation and mitigation strategies must be implemented quickly if plans are to be in place by mid-century. GCM data suggests that more robust rainfall regime changes may be delayed until end-century (e.g. Trenberth, 2011). However, those GCMs are likely unable to resolve some of the key aspects of cloud and rainfall production in EYNF, most notably the sensitivity to moisture loading at low-levels and orographically driven ascent.

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